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The Latent Structure of Fluid Intelligence: A Factor Analytic Investigation of Attentional Control, Speed of Information Processing, and Working Memory

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Abstract

This study aimed to evaluate attentional control, information processing speed, working memory capacity, and fluid intelligence among 62 Saudi Arabian university students using a battery of cognitive tasks. Significant positive correlations, ranging from .22 to .41, were observed between performance on specific cognitive tasks and fluid intelligence. These findings are consistent with the general factor model of intelligence, as all variables demonstrated substantial loadings on a single factor accounting for 52.6% of the variance in task performance. The significance of this study lies in its status as one of the rare investigations that have attempted to validate the general factor hypothesis within Arab samples.

Keywords: Elementary cognitive tasks, Information processing speed, Working memory, Fluid intelligence

1 Introduction

According to Spearman's theory of human intelligence (Duffy et al., 2019), there are two components that contribute to overall cognitive abilities: a general factor, and specific factors. The specific factor refers to the unique abilities that an individual possesses to perform a particular cognitive task. These specific abilities account for differences in the performance on different tasks. The general factor, on the other hand, also known as general intelligence or *g*, describes how consistent the performance is across different cognitive tests. The *g* construct explains the high correlations between subtests of intelligence, indicating that there is a common factor underlying all cognitive abilities (I. J. Deary et al., 2021).

Cattell expanded on the general factor hypothesis, proposing that general intelligence can be divided into two basic factors: crystallized and fluid intelligence (Brown, 2016). Crystallized intelligence refers to all the learned information that is stored in long-term memory and is accumulated through education, training, and life experiences. In contrast, fluid intelligence refers to the ability to reason with novel information independently of previous experiences and practices. Fluid intelligence is particularly important for problem-solving, abstract thinking, and learning new information that is not related to prior knowledge or experiences.

The Raven's Standard Progressive Matrices (SPM) is a widely used psychometric scale designed to measure fluid intelligence (Hiscock, 2006). The SPM evaluates an individual's capacity to perceive and analyse abstract visual patterns and relationships, deduce underlying principles, and solve novel abstract problems. The test presents a series of visual matrices with a missing element, and the test-taker is required to select the correct missing element from a set of alternatives. Its design minimizes the impact of acquired knowledge and cultural background, making it a valuable tool for assessing *g* factor and fluid intelligence.

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Subsequent researchers focused their attention on elucidating the variations observed within the general factor, focusing on identifying the key variables underlying individual differences. The information processing speed approach posits that an individual's initial processing speed, reflecting his or her capacity to encode input prior to its decay or interference from subsequent stimuli, constitutes a significant determinant of individual variability in intelligence (Hunt, 2010; Jensen, 1993, 1998; Mackintosh, 2011; Schubert et al., 2017; Vernon, 1985). Proponents of this approach suggest that biological variations in neural conduction efficiency in the brain account for individual differences (I. J. Deary, 2000; Jensen, 1982; P. Vernon, 1983). Empirical evidence supports the claim that there is a correlation between measures of information processing speed and intelligence measured with both timed and untimed intelligence tests (P. A. Vernon, 1985). Individuals with faster simple reaction times tend to exhibit higher intelligence (Deary, 2000; Deary et al., 2010). Individuals identified as gifted or possessing above-average cognitive abilities demonstrate superior information processing speed compared to their peers with typical or below-average cognitive profiles (Kranzler et al., 1994; Miller & Vernon, 1996).

Furthermore, research indicates that enhanced information processing speed in early life correlates with higher general intelligence at a later time (Rose et al., 2012). Age-related declines in information processing speed have been observed in adults (Kail, 2007; Salthouse et al., 1998), while age-related increases have been noted in children (Anderson et al., 1997; Rose & Feldman, 1997). Individual differences in processing speed in old age are predicted to some extent by childhood cognitive ability (Deary et al., 2010). Studies have also reported differences in information processing speed across demographic groups, with some studies suggesting potential variations related to sex (Jorm et al., 2004), ethnicity (Jensen, 1969; P. A. Vernon & Jensen, 1984), and race.

Working memory capacity is increasingly posited as a more direct determinant of individual differences in fluid intelligence. Grounded in Baddeley's multicomponent model (Chai et al., 2018), working memory involves the active processing of information within short-term stores—namely the phonological loop and the visuospatial sketchpad—which serves as the cognitive foundation for complex reasoning and problem-solving. Supporting this, research by Kyllonen and Christal (1990) showed a high correlation between reasoning ability scores and working memory performance, suggesting a strong link between these cognitive abilities (Kane & Engle, 2002). Consequently, Colom and colleagues (2008) observed a robust correlation between working memory capacity and intelligence (Gonthier, 2014). However, the construct validity of working memory remains a subject of debate, leading to inconsistent findings in some prior investigations. Working memory is variably conceptualized as a unitary construct, assessed through an overall score, or as a multifaceted construct encompassing distinct verbal and visuospatial processing components. Furthermore, certain tasks may introduce confounding effects due to the inclusion of information processing speed demands. Nonetheless, the consistent and robust correlations observed between working memory capacity and general intelligence provide compelling evidence for the notion that working memory is a fundamental cognitive mechanism underlying individual differences in IQ (Kovacs et al., 2019; Shipstead et al., 2016).

The strong correlation observed between working memory capacity and the general factor of intelligence may be attributed to the facilitative role of efficient information processing, which mitigates the cognitive load imposed by the limited capacity of working memory, thereby releasing cognitive resources for other mental operations (Evans et al., 2024; Krieglstein et al., 2022). Developmental changes in both working memory capacity and information processing speed also exert an influence on general intelligence (Dimitriou et al., 2002; Kail et al., 2015).

A dichotomy exists between automatic and controlled information processing, with the former characterized by rapid and effortless execution and the latter by deliberate and effortful processing (Schneider & Chein, 2003). Theoretical frameworks, such as Muller et al. (2026), propose that controlled and automatic processes may exist along a continuum, whereby practice leads to gradual performance enhancement, accelerated learning, diminished reliance on attentional control, and the liberation of attentional resources for other cognitive pursuits.

A substantial body of research investigating the cognitive underpinnings of individual differences in general intelligence predominantly employs elementary cognitive tasks that rely heavily on automatic processing, such as simple reaction time, choice reaction time paradigms (I. J. Deary, 2000; Der & Deary, 2003; Jensen, 2006; Sheppard & Vernon, 2008), and inspection time (Kranzler et al., 1989; Nettelbeck, 1982). The strength of the correlations observed between intelligence and performance on these elementary cognitive tasks tends to increase proportionally with complexity of the elementary cognitive task (Kranzler & Jensen, 1991; Schubert, Hagemann, & Frischkorn, 2017), suggesting that cognitive processing efficiency plays a significant role in shaping individual differences in general intelligence. However, the precise nature of the relationship between automatic and controlled processing and intelligence remains an area that warrants further empirical investigation.

It is noteworthy that research investigating the existence of the general factor of intelligence and its underlying components within the Arab context is relatively scarce (Breit et al., 2022), the majority of studies relying on culture-fair assessments such as the Raven's Progressive Matrices (Abdel-Khalek & Raven, 2006). The relationship between performance on these measures of general intelligence and other cognitive domains has not been extensively explored (Alasali, 2021).

Despite the wealth of international research on the cognitive correlates of fluid intelligence, the majority of these studies have been conducted within WEIRD (Western, Educated, Industrialized, Rich, Democratic) populations, leaving questions of generalizability unanswered (Breit et al., 2022). This study is particularly relevant as it provides empirical evidence from a Saudi Arabian context, a region underrepresented in cognitive psychometric literature. By examining these relationships in a different cultural and linguistic setting, we can test the cross-cultural robustness of established cognitive models (Albawardi et al., 2022; Tan et al., 2022).

2 Aims of the study

The current study aims to address the following research question: To what extent do attentional control, information processing speed, and working memory capacity predict fluid intelligence in a Saudi student sample?

An additional critical dimension in contemporary psychometric research is the observation of secular trends in intelligence, widely known as the Flynn Effect. This phenomenon refers to the substantial and sustained increase in IQ scores observed across the 20^{th} century in various parts of the world (Trahan et al., 2014). While recent data suggest that these gains may be plateauing or even reversing in many Western nations (Mingroni, 2010), developing regions—including the Arab world—continue to show significant increases in cognitive performance (Almoghyrah et al., 2025). In Saudi Arabia specifically, previous longitudinal comparisons have documented notable IQ gains over the past few decades, attributed to rapid societal shifts and improvements in the quality of education (Almoghyrah et al., 2025). Therefore, comparing the cognitive performance of the current sample with historical Saudi data is essential not only for validating the general factor of intelligence, but also for providing insights into the trajectory of cognitive development and secular trends within the Kingdom.

3 Method

3.1 Participants

Participants in this study were 62 individuals who were enrolled in the psychology department at King Saud University. They ranged in age from 18 to 22 years, with a mean age of 20.7 and a standard deviation of 1.33. All participants provided their informed consent to participate in the research conducted at the laboratories of the King Saud University psychology department.

3.2 Tools

Raven's standard progressive matrices plus (SPM+)

Raven's Progressive Matrices are considered one of the most accurate scales in assessing the general factor of intelligence (Davydov & Chmykhova, 2016). This scale is recognized for its culture-fair design, minimizing the influence of specific cultural or educational backgrounds on the assessment of cognitive abilities (Garcia et al., 2021). The researchers employed the standardized scoring procedures and applied normative data based on British standards, as the present study did not aim to establish norms for the Saudi population. Notably, numerous cross-cultural investigations involving Arab samples have utilized similar methodological approaches with various adaptations of this test (Abdel-Khalek, 1988; Essa et al., 2016). The current study utilized the Standard Progressive Matrices Plus (SPM+) (te Nijenhuis et al., 2019; Pahor et al., 2018). This measure is associated with general intelligence (*g*), irrespective of verbal or non-verbal components (Takeuchi et al., 2012).

Participants' general mental ability was evaluated using Raven's Standard Progressive Matrices Plus (SPM+). The SPM+ was employed in this study due to its enhanced psychometric capacity to discriminate effectively across higher-ability intellectual echelons while maintaining structural continuity. Furthermore, the selection of this tool aligns with previous Arabic literature that has successfully utilized it within regional contexts. To ensure rigorous quantification of cognitive performance, participants' raw scores were converted into standardized Intelligence Quotient (IQ) values utilizing the original British standardization norms

Stroop colour naming task

The Stroop Colour-Naming Task is a well-established neuropsychological test employed for both experimental and clinical purposes (Scarpina & Tagini, 2017). It is designed to assess an individual's ability to inhibit cognitive interference, which arises when the processing of one stimulus feature interferes with the concurrent processing of another (Stroop, 1935).

In this task, participants are typically presented with three conditions. In two of these, representing congruent conditions, participants are instructed to name colours printed in black ink and to name different colour patches. In the third condition, the incongruent condition, participants are presented with stimulus-conflict words (e.g., the word 'red' printed in green ink) and colour patches. Participants are instructed to name the ink color of the letters while suppressing the automatic tendency to read the word. This incongruent condition requires performing a less automatic task (naming the ink colour) while inhibiting interference from a more automatic task (reading the word), which slows their reaction time (for review, Cohen et al., 1992; MacLeod, 1991; Scarpina & Tagini, 2017).

The Stroop Colour-Word Test (SCWT) is commonly utilized to measure inhibitory control and other cognitive functions, including attention, processing speed, cognitive flexibility, and working memory (Scarpina & Tagini, 2017). In this study, researchers administered a computerized version of the SCWT.

Posner's letter matching task

In this letter-matching task, participants are presented with pairs of letters from the alphabet and must determine whether the letters are the same or different. Researchers may base the criteria for similarity on either identity (e.g., A, A) or case (e.g., A, a). This task is often used to investigate cognitive processes such as response selection and the speed of information retrieval from long-term memory (for review, Posner & Petersen, 1990; Sheppard & Vernon, 2008).

In this study, researchers administered a computerized version of a letter-matching task, adapted from Posner's paradigm, with each trial presenting a pair of letters. Two experimental conditions were employed. In the identity condition, letter pairs matched in both case and identity (e.g., B, B); in the case-match condition, letter pairs were matched in identity but differed in case (e.g., B, b). On each trial, participants were instructed to provide a response as quickly as possible, using a designated response key to indicate whether the letter pairs matched (e.g., right key) or did not match (e.g., left key).

Processing efficiency task

The cognitive processing efficiency task, as described by Burgaleta and Colom et al. (2008), requires participants to perform simple arithmetic operations, specifically addition and subtraction. Across ten trials, participants are instructed to evaluate the accuracy of provided arithmetic solutions. Each trial commences with the presentation of an arithmetic problem, designated as Task X (e.g., 5 + 4 = 9). Participants are required to indicate the correctness of the solution by pressing a designated response key and to retain the problem and its solution in working memory, regardless of accuracy. Subsequently, a second arithmetic problem, designated as Task Y (e.g., 6 + 2 = 9), is presented. Participants again indicate the correctness of the solution and retain the problem and its solution. In the final phase of each trial, participants are presented with a third arithmetic problem, designated as Task XY (e.g., X + Y = 18), and are required to evaluate the accuracy of the solution based on the previously presented Tasks X and Y.

The processing efficiency task requires participants to execute simple arithmetic operations while maintaining accuracy across multiple stages. To ensure a precise measurement of processing efficiency, the analysis focused exclusively on the mean reaction time for correct trials. By filtering out incorrect responses, this metric serves as an indicator of cognitive speed (Rutter et al., 2020), reflecting the individual's ability to efficiently process and retain information in working memory—specifically Tasks X and Y—to successfully solve the final integration in Task XY.

The design of this task aims to maintain a consistent cognitive load on short-term memory across all trials (Oberauer et al., 2018). Therefore, observed differences in performance are posited to reflect individual variations in processing efficiency, independent of working memory (Colom et al., 2006). Furthermore, the task is designed to assess participants' ability to focus attention on sequential processing events and to retain relevant task-related information (Burgaleta & Colom, 2008).

Working memory capacity task

This task assesses participants' working memory capacity by requiring them to retain and recall the solutions to a varying number of arithmetic problems across trials. At the start of each trial, an arithmetic problem (e.g., 3 + 4 = 7) is presented, and participants are instructed to evaluate the accuracy of the solution and maintain it in working memory, regardless of its correctness. Each trial varies in the number of arithmetic problems presented, ranging from 3 to 7. Following the presentation of the final problem in each trial, participants are required to recall and record the solutions to all presented problems in the order of their occurrence. The arithmetic problems are intentionally simple, involving only addition and subtraction, with solutions ranging from 1 to 9.

This working memory capacity task differs from the previously described processing efficiency task in its primary focus on the ability to maintain and retrieve information in the presence of increasing cognitive load. Specifically, the working memory task requires participants to retain a variable number of items (3-7) for subsequent recall, thus directly manipulating the demands on working memory storage.

3.3 Materials

A computer equipped with E-Prime 2.0 software, a platform designed for the creation and execution of behavioural experiments, presented the experimental stimuli (Karagüzel & Erdoğdu, 2025).

3.4 Procedures

The study employed a two-session protocol. In the initial session, participants completed the Raven's Standard Progressive Matrices (SPM) to assess their fluid intelligence (Bilker et al., 2012). In the subsequent session, participants performed the elementary cognitive tasks. Tasks were administered to participants under counterbalanced conditions to control for the confounding effect of task order. Before administering the experimental tasks, participants completed a series of practice trials to familiarize themselves with the task demands and trial procedures. This procedural step minimized participant attrition and ensured data integrity. All tasks were presented via computer, encompassing performance instructions, trial parameters, break intervals, task guidelines, stimulus presentation durations, warm-up periods, task sequencing, trial conditions, response recording, and the automatic calculation of accuracy and response times.

3.5 Data analysis

Statistical analyses were conducted using IBM SPSS Statistics. Prior to the main analyses, the data were screened for missing values and univariate outliers. Descriptive statistics, including means, standard deviations and measures of distributional normality, were calculated for all cognitive performance variables and intelligence scores. To evaluate the latent structure of the cognitive tasks and address the general factor hypothesis, an exploratory factor analysis was conducted using principal component analysis. This 'basic' yet essential psychometric procedure was employed to determine if the fluid intelligence measure (SPM+) and the cognitive tasks (attentional control, working memory, and speed) converge on a single underlying factor. The suitability of the data for factorization was assessed using the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity (Unsworth et al., 2014). Factors were extracted based on eigenvalues greater than 1, consistent with standard intelligence research protocols.

To examine the primary relationships between fluid intelligence, attentional control, information processing speed, and working memory, Pearson correlation coefficients were computed. In accordance with the American Psychological Association and Association for Psychological Science recommendations to prioritize effect sizes over mere significance levels, the magnitude of these correlations was interpreted using Cohen's benchmarks: small, modest/medium, and large.

Following the correlational analysis, a multiple linear regression was performed to determine the extent to which attentional control and working memory tasks uniquely predict variance in standardized IQ scores derived from the SPM+. This analysis allows for the assessment of whether attentional control remains a robust predictor of intelligence when accounting for other cognitive capacities.

Finally, to address the potential for secular trends (the Flynn Effect), the IQ scores obtained from the current Saudi sample were compared with historical performance data from studies in the region (Almoghyrah et al., 2025; Batterjee, 2011). Independent samples t-tests were used to identify significant differences in mean scores across decades, facilitating an exploration of cognitive development trajectories within the Saudi Arabian educational context (Alasali, 2021; Almoghyrah et al., 2025; Batterjee, 2011).

4 Results

The relationships between variables were examined using Pearson's correlation coefficient (Table 1). When interpreting these effect sizes in the context of broader psychometric literature, the correlations observed in the current Saudi sample appear somewhat lower than those reported in large-scale meta-analyses. For instance, Kane et al. (2005) reported a median correlation between working memory capacity and fluid intelligence of .72 across 14 data sets. Our observed correlation (.26) is considerably smaller than this. This discrepancy may be attributed to our use of specific task-level scores rather than a latent-variable approach, which typically yields much higher correlations (often ranging from .60 to .85) by minimizing task-specific variance (Kane et al., 2005). However, our Stroop-intelligence correlation (.419) is comparable to effects found in other executive function studies, where attentional control is identified as a robust predictor of fluid intelligence (Cochrane et al., 2019; Unsworth et al., 2014).

The modest nature of these correlations suggests that while the cognitive architecture of Saudi students aligns with the general factor model, the shared variance between these specific elementary tasks may be influenced by sample-specific characteristics or the controlled laboratory environment.

The bivariate correlation analysis revealed a nuanced pattern of relationships among the targeted cognitive measures. Standardized IQ scores demonstrated statistically significant positive associations with attentional control efficiency (r = .35, p = .005) and working memory performance (r = .26, p = .041). Conversely, significant negative correlations were observed between standardized IQ scores and performance indices on both the Stroop task (r = -.42, p = .001) and the Posner task (r = -.22, p = .082). It

Table 1: Descriptive statistics and correlations among attentional control, speed of recall from long-term memory, working memory capacity, and fluid intelligence (with *p* values in parentheses)

	Descriptives			**Correlations**			
	Mean	**SEM**	**SD**	**1**	**2**	**3**	**4**
1. Intelligence	103.52	1.286	10.128				
2. Efficiency	0.808	0.024	0.188	0.350** (0.005)			
3. Working	3.111	0.132	1.038	0.261* (0.041)	0.142 (0.270)		
4. Stroop	1.191	0.040	0.318	-0.419** (0.001)	-0.377** (0.003)	-0.310* (0.014)	
5. Posner	0.759	0.043	0.339	-0.223 (0.082)	-0.433** (0.000)	-0.477** (0.000)	0.438** (0.000)

Note. Fluid intelligence was assessed using Raven's Standard Progressive Matrices Plus (SPM+), with raw scores converted into standardized IQ scores based on the original British standardization norms.
* $p < .05$, ** $p < .01$, *** $p < .001$

is critical to note that the negative signs of the latter correlation coefficients are an artefact of the scoring methodology, as performance on the Stroop and Posner tasks is quantified as reaction times; thus, lower reaction latencies inherently denote superior cognitive proficiency. Furthermore, the correlation between attentional control efficiency and working memory performance did not reach statistical significance (r = .14, p = .270). Rather than relying strictly on significance thresholds, the interpretation of these cognitive correlates of fluid intelligence focused primarily on the magnitude of effect sizes to ascertain the practical and theoretical robustness of the observed relationships, which aligned with Cohen's criteria across a spectrum of small to large effects (Owens et al., 2021).

4.1 Correlational analysis and effect sizes

The strongest relationship observed in the Saudi sample was between the Stroop task (attentional control) and fluid intelligence, which yielded a **medium-to-large effect size** (r = -.419, p = .001). This suggests that a substantial portion of the variance in intelligence scores is shared with the ability to inhibit interference and maintain executive control (Cochrane et al., 2019; Unsworth et al., 2014). A medium effect size was also demonstrated between processing efficiency and standardized IQ scores (r = .35, p = .005). This indicates that the speed and efficiency of information processing are moderate predictors of general mental ability in this population (Alasali, 2021; Cochrane et al., 2019).

The relationship between working memory capacity and fluid intelligence demonstrated a small-to-medium effect size (r = .26, p = .041). While this correlation is lower than the large effects (often $r \geq .50$) reported in Western studies using latent-variable modeling, it remains a reliable predictor within the task-specific constraints of the current study (Kane et al., 2005). Finally, the Posner task showed a small-to-medium negative correlation with intelligence (r = -.22, p = .082), representing the weakest effect size among the measured variables.

An exploratory factor analysis (EFA) using principal components analysis examined the underlying factor structure of the attention control, information processing speed, working memory capacity, and fluid intelligence tasks (Table 2). Prior to conducting the EFA, the factorability of the data was assessed by using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was 0.665, exceeding the minimum acceptable threshold of 0.6, indicating sampling adequacy. Bartlett's test of sphericity yielded a statistically significant chi-square value of 44.90 ($p < .01$), leading to the rejection of the null hypothesis and supporting the suitability of factor analysis. The EFA revealed a single-factor solution, with all tasks showing substantial loadings on this factor (ranging from 0.652 to 0.834) and an eigenvalue of

Table 2: Factor loadings and variance explained

Cognitive measures	Factor loading (general factor)	Initial Eigenvalues (total)	% variance	Cumulative %	Total
Efficiency	0.663	2.105	52.635	52.635	2.105
Working memory	0.652	0.869	21.725	74.360	
Stroop (latency)	-0.739	0.603	15.079	89.440	
Posner (latency)	-0.834	0.422	10.560	100.00%	

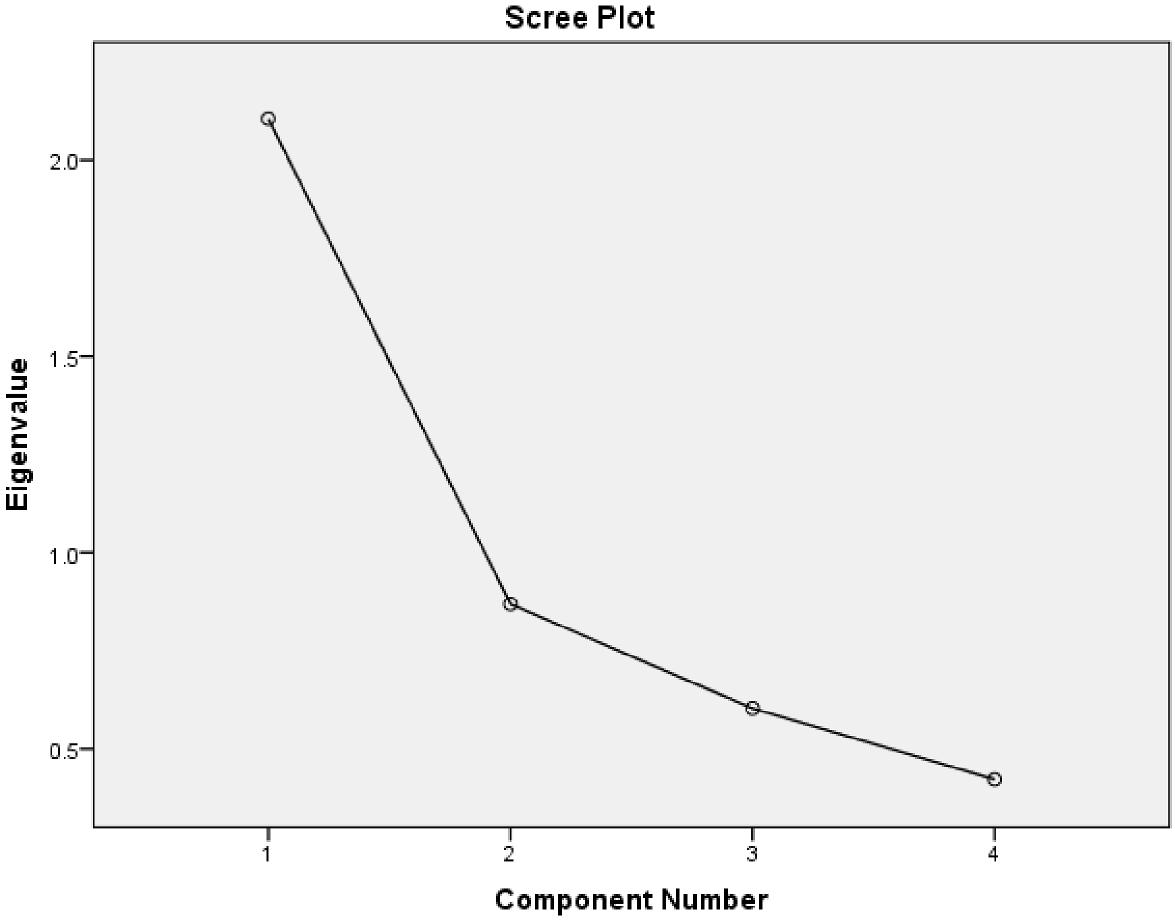

Figure 1: Scree plot showing the eigenvalues resulting from the analysis

2.105. This single factor accounted for 52.63% of the total variance. The scree plot further supported the appropriateness of the single-factor solution (Figure 1).

4.2 Comparative secular trends

In evaluating the current sample's performance against historical Saudi data, we observed a notable increase in mean IQ scores, reflecting a clear **secular trend** (Almoghyrah et al., 2025; Batterjee, 2011). The magnitude of this increase (approximately 0.3 to 0.5 IQ points per year) is comparable to gains reported in other developing regions and underscores the ongoing trajectory of cognitive development in the Kingdom (Almoghyrah et al., 2025; Bakhiet et al., 2014).

5 Discussion

The results of the current study provide moderate to strong support for our primary research hypotheses. Specifically, our first hypothesis regarding the replication of classical cognitive findings in a Saudi sample was confirmed, as we observed significant correlations between fluid intelligence, working memory, and attentional control (Kane et al., 2005; Unsworth et al., 2014). Our second hypothesis was also supported, with attentional control emerging as a robust predictor of fluid intelligence (Gf; r = -.419, p = .001), consistent with the 'executive attention' framework (Cochrane et al., 2019; Unsworth et al., 2014). Finally, our third hypothesis was confirmed by the significant relationship between processing efficiency and intelligence (r = .35, p = .005), thereby consolidating the widely recognized paradigm that positions information processing speed as a pivotal correlate of fluid intelligence (Cochrane et al., 2019). While the observed effect sizes in this Saudi context were somewhat lower than those reported in Western latent-variable studies (Alasali, 2021), the consistent pattern of correlations across all tasks validates the cross-cultural robustness of the general factor model.

The current study demonstrated significant correlations between performance on all elementary cognitive tasks and fluid intelligence, with the absolute magnitude of correlation coefficients ranging from .22 to .42. These findings align with a substantial body of prior research that has consistently reported associations between performance on elementary cognitive tasks and fluid intelligence (for a review, see Sheppard and Vernon, 2008).

The statistically significant correlations observed between the elementary cognitive tasks and fluid intelligence provide empirical support for the hypothesis that the general factor of intelligence is a robust construct, measurable across a variety of cognitive tasks (Conway et al., 2003; Deary, 2000; (Kyllonen & Christal, 1990). These findings further substantiate the existence of a general factor of intelligence that underlies individual differences in cognitive abilities. It should be noted that traditional intelligence batteries, such as the Wechsler scales, do not equally assess executive control abilities such as inhibiting pre-potent responses and shifting mental sets, which are critical for attentional control and interference inhibition (Friedman et al., 2006). While these tests assess working memory capacity and processing speed as isolated constructs, they often overlook the "processing dynamics" involved in suppressing task-irrelevant information during cognitive performance (Engle & Kane, 2004; Engle et al., 1999). Current research suggests that cognitive efficiency is not merely a function of raw capacity, but rather depends on executive functions responsible for managing interference—core components that remain underrepresented in standardized IQ scores (Barkley, 2012; Friedman & Miyake, 2004).

The negative correlation observed between Stroop task performance speed and fluid intelligence (-.419) is consistent with the task's established role in measuring inhibitory control, which is the ability to suppress cognitive interference (e.g., (Cohen et al., 1990; Scarpina & Tagini, 2017). As posited by Stroop (1935), cognitive interference arises when the processing of one stimulus feature interferes with the concurrent processing of another feature within the same stimulus. This interference is attributed, in part, to limitations in the human information processing system, specifically the constrained capacity for simultaneous stimulus processing (e.g., (Broadbent, 1957; Schneider & Shiffrin, 1977).

Optimal performance on tasks involving complex cognitive processing and stimulus competition necessitates a degree of executive attentional control. This cognitive control mechanism enables individuals to selectively attend to task-relevant stimulus dimensions while inhibiting the processing of irrelevant dimensions (Cohen et al., 1990; Cohen et al., 1992). In a seminal early review, Jensen and Rohwer (1966) reported that performance on the Stroop task demonstrates reliable predictive validity for individual differences on a range of complex psychological assessments. Additionally, Golden (1975) proposed that the Stroop task is a valuable instrument for assessing creative abilities, citing its capacity to elucidate key cognitive processes, its temporal stability, and its ease of administration. The results of his study demonstrated a statistically significant correlation between the speed of performance on the Stroop task and performance on both verbal and non-verbal creativity tasks, as well as teachers' evaluations of students' creativity. Arafa (2007) reported a positive correlation between Stroop task performance and general intelligence scores, which aligns with the current study's finding of a relationship between Stroop task performance and fluid intelligence.

The remaining three cognitive tasks—the Posner task (*r* = -.223), the processing efficiency task (*r* = .350), and the working memory capacity task (*r* = .261)—also exhibited significant correlations with fluid intelligence, albeit with varying degrees of strength and statistical significance.

The Posner task is described as an elementary cognitive task that measures the speed of information retrieval from long-term memory, and the results of numerous studies indicate a statistically significant correlation between the speed of performance on this task and general intelligence (e.g., (Posner & Petersen, 1990; Sheppard & Vernon, 2008). Although the correlation between Posner task performance and fluid intelligence did not reach statistical significance in the current study, it was nonetheless negative (*r* = -.223). This suggests a trend in which faster information processing speed, as indexed by the Posner task, is associated with higher fluid intelligence. The ability to retrieve information quickly and efficiently from long-term memory is likely to be an important cognitive process that contributes to individual differences in fluid intelligence (Li et al., 2004; Rockstroh & Schweizer, 2001).

The processing efficiency task employed in this study required participants to maintain information in short-term memory across all experimental trials, with observed differences in performance reflecting processing efficiency independent of working memory capacity. Specifically, participants were instructed to accurately perform simple arithmetic operations while concurrently maintaining the results in short-term memory for a brief duration. Furthermore, the task assessed attentional control by requiring participants to focus on task-relevant information while disregarding irrelevant information (Derakshan & Eysenck, 2009). The Stroop task primarily engages automatic processing, but also involves controlled processing (Brunetti et al., 2021). Moreover, both tasks require the inhibition of interfering information unrelated to the main task, while simultaneously processing task-relevant information and retaining it in working memory (Endres et al., 2015; Long & Prat, 2002).

Although the correlation coefficient between working memory capacity and general intelligence was not high in this study, it was positive and statistically significant, consistent with the results of studies that collectively indicate that working memory is a fundamental component of the variance in general intelligence (e.g., (Carpenter et al., 1990; Conway et al., 2002; Engle et al., 1999; Kyllonen & Christal, 1990). Whether general working memory capacity or the efficiency of specific working memory components is the primary driver of individual differences in intelligence remains a key debate (Carpenter et al., 1990; Engle et al., 1999; Kyllonen & Christal, 1990). Crucially, the strong link between working memory capacity and performance across diverse cognitive tasks highlights its fundamental role in explaining variations in general cognitive ability (Ackerman et al., 2005; Carpenter et al., 1990; Colom et al., 2008; Colom & Chun Shih, 2004). Across several studies, the correlation between comprehensive measures of both working memory capacity and general cognitive ability has been reported to range from 0.80 to 0.90 (e.g., (Kyllonen & Christal, 1990). This suggests that the correlation between working memory capacity and general intelligence is substantially more robust when measured through a diverse battery of cognitive tasks. Utilizing a latent-variable approach—which aggregates results from multiple working memory tests and diverse intelligence subtests—effectively minimizes task-specific variance and measurement error. This methodological rigor provides a more precise representation of the underlying cognitive architecture, confirming that working memory is a fundamental constituent of the variance in general intelligence (Kane et al., 2005).

Furthermore, the observation that all variables exhibited substantial loadings on a single factor lends support to the general factor theory of intelligence. Notably, the participants' performance on the processing efficiency and working memory capacity tasks showed negative loadings on the general factor (-0.663 and -0.652, respectively), while their performance on the Stroop color-naming and Posner long-term memory retrieval tasks showed high loadings on the same factor (0.739 and 0.834, respectively). This pattern suggests that the general factor primarily reflects the speed of information processing, a finding consistent with previous research (e.g., (I. Deary, 2001; Jensen, 1998; P. Vernon, 1983). Nonetheless, it appears that the extraction of a general factor is fundamentally dependent on the nature and number of subtests measuring processing speed relative to those assessing working memory capacity and abstract analytical reasoning. Consequently, the subtests that are most representative of the overall battery will tend to exhibit the highest loadings on the general factor.

The highest factor loadings on the general factor were observed for the Posner and Stroop tasks, emphasizing the critical role of cognitive processing mechanisms inherent in these tasks that account for individual differences in the general factor. These mechanisms, including information processing speed, attentional control and semantic activation, appear to significantly contribute to the variance in the general factor. This finding aligns with Conway et al. (2002)'s proposition that the relationship between elementary cognitive tasks and fluid intelligence is mediated by attentional control and working memory processes. Our results indicate that the positive correlation between working memory capacity and fluid intelligence, in addition to the high factor loadings of processing speed tasks, is partly attributable to attentional control, a function performed by the central executive component of working memory. This component helps to inhibit task-interfering information and keep task-relevant information active and under mental processing (e.g., (Engle, 2018; Engle et al., 1999).

Table 1 presents descriptive statistics indicating a mean IQ score of 103, with a standard deviation of 10.1 for the Saudi university student sample in the current study. These results diverge significantly from prior IQ assessments conducted in North African and Arab populations, which have reported mean IQ scores of approximately 84 (Kanazawa, 2004; Parra & Kirkegaard, 2025; Rushton & Jensen, 2010). The present study reveals a significant increase of 19 IQ points among Saudi university students compared to previously reported values. Notably, both the current findings and prior research on Arab populations suggest a trend of increasing IQ across generations. For example, Batterjee et al. (2013) compared the cognitive performance of Saudi schoolchildren between 1977 and 2010, reporting an 11.7-point increase in IQ, with an average increase of 3.55 points per decade. Abdel-Khalek (1988) examined gender differences in intelligence among Alexandria University students using the Standard Progressive Matrices test, finding mean IQ scores of 81 for males and 78 for females. In 2000, Abdel-Khalek et al. (2014) replicated the study with Ain Shams University students (586 males, 1,561 females), revealing mean IQ scores of 87 for males and 81 for females, indicating a statistically significant increase in IQ for both genders between the two studies. Another study by Abdel-Khalek et al. (2015) on 2,147 Ain Shams University students, across scientific and literary disciplines, demonstrated a further increase in IQ. Using the Advanced Progressive Matrices test, they reported a mean IQ of 89.5 for the overall sample, with scientific majors exhibiting higher mean IQ (94.5) than literary majors (87). Male students displayed a higher mean IQ than female students, with a minor difference of 1.2 IQ points. This negligible variance aligns with previous research suggesting no significant gender differences in general cognitive ability (Giofrè et al., 2022; Giofrè et al., 2024; Reilly, 2012)

Similarly, a study by Essa et al. (2016) found that IQ scores increased in Egypt (Alasali, 2021). Abdel-Khalek and Lynn (2016) conducted a study in 2015, assessing intelligence with the Standard Progressive Matrices Plus, which reported mean IQ scores of 104 for males and 92 for females in a sample of 423 students at Alexandria University (Abdel-Khalek & Lynn, 2016). The mean IQ score of 103 obtained for Saudi students in the current study is comparable to the mean IQ of 104 reported for Egyptian university students, particularly considering the current study's exclusion of female participants. These findings collectively indicate an upward trend in IQ scores within Arab populations over time (Alasali, 2021), suggesting that further research is warranted to elucidate the contributing factors.

The current study's findings are consistent with a substantial body of research documenting significant increases in IQ scores in developing societies (e.g., (Abdel-Khalek & Lynn, 2016; Batterjee et al., 2013; Colom et al., 2007; Daley et al., 2003; Essa et al., 2016; Meisenberg et al., 2006; Rindermann, 2024). However, a recent meta-analysis by Pietschnig and Voracek (2015) highlights that while IQ scores are generally increasing globally, this trend is not uniform across all nations and varies across different domains of intelligence (Pietschnig & Voracek, 2015). Lynn and Hampson (1986) provided early evidence of this variability, demonstrating differential rates of IQ increase across Britain, Japan, and the United States, with a greater increase in non-verbal than verbal intelligence in Britain and the United States, but inconsistent findings in Japan (Sauce & Matzel, 2017). Similarly, IQ gains in children measured by the WISC-III and WISC-IV in Taiwan were 2.45 IQ points per decade over 1997-2007, with greatest gains in visual-spatial abilities and smallest gains in verbal abilities (Chen et al., 2013).

These findings underscore the importance of employing diverse intelligence measures and expanding research samples to encompass diverse ethnic groups in future investigations. It is imperative to utilize a broader range of cognitive tasks that represent various levels of the general factor, to address the issue of non-uniform IQ increases across different intelligence domains and countries. Recent observations suggest a paradoxical trend where rising psychometric IQ scores coexist with declining performance in elementary cognitive tasks, such as reaction times (Holden et al., 2020; Woodley of Menie et al., 2015). As Woodley et al. (2013); have noted, there are significant reports of worsening reaction times despite the historical trend of rising IQ scores (Woods et al., 2015). These results strongly suggest that a broader range of cognitive abilities—specifically different facets of working memory and processing speed—must be examined to understand secular trends, as our current knowledge of the Flynn effect on these specific domains remains limited.

Furthermore, it is crucial to consider factors such as advancements in education, nutrition, and healthcare, which may contribute to observed IQ gains. By accounting for these factors, future research can provide a more comprehensive understanding of the Flynn effect. As a first step, we must determine whether the Flynn effect is continuing. Results from Europe (and most recently America) indicate that the Flynn effect is ending in the most advanced countries (Trahan et al., 2014; Woodley & Meisenberg, 2012). It is hoped that the Flynn effect is continuing in less developed countries, but this requires empirical study (e.g., Pietschnig & Voracek, 2015).

6 Conclusion

In conclusion, the present study's findings are consistent with prior research, particularly regarding the existence of a general factor of intelligence and the correlations observed between various primary cognitive tasks and fluid intelligence, which ranged from 0.22 to -0.41. The Stroop and Posner tasks, assessing attentional control and processing speed, respectively, exhibited stronger loadings on the general factor, suggesting that information processing speed plays a crucial role in individual differences in general intelligence.

Furthermore, the study revealed a substantial increase in the IQ scores of Saudi university students compared to previous estimates. These findings are congruent with other studies documenting significant increases in IQ scores within developing societies (Daley et al., 2003; Saad Almoghyrah et al., 2025). However, it is important to acknowledge that IQ increases are not uniform and may vary across different domains of intelligence and geographical regions (Pietschnig & Voracek, 2015).

Overall, the current study's results contribute to a more nuanced understanding of the factors influencing individual differences in general intelligence and highlight the necessity of employing diverse measures of cognitive ability in future research. Additionally, the findings offer valuable insights into the cognitive profiles of Saudi university students and underscore the importance of continued efforts to support cognitive development within this population.

7 Limitations

It is crucial to acknowledge several limitations inherent in the present study. Firstly, the individual administration of elementary cognitive tasks within a controlled laboratory setting, coupled with the voluntary nature of participant involvement, may have constrained both the sample size and its representativeness. Secondly, the elementary cognitive tasks employed did not comprehensively encompass all domains of general cognitive ability, potentially limiting the overall scope of the findings.

Consequently, the current study's results provide preliminary indicators supporting the general factor hypothesis within a novel contextual framework. Future research employing larger, more representative samples and a comprehensive battery of cognitive tasks that span various levels of general cognitive ability, are anticipated to yield more generalizable results. These investigations will further validate the hypothesis and provide deeper insights into the determinants of individual differences in intelligence.

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